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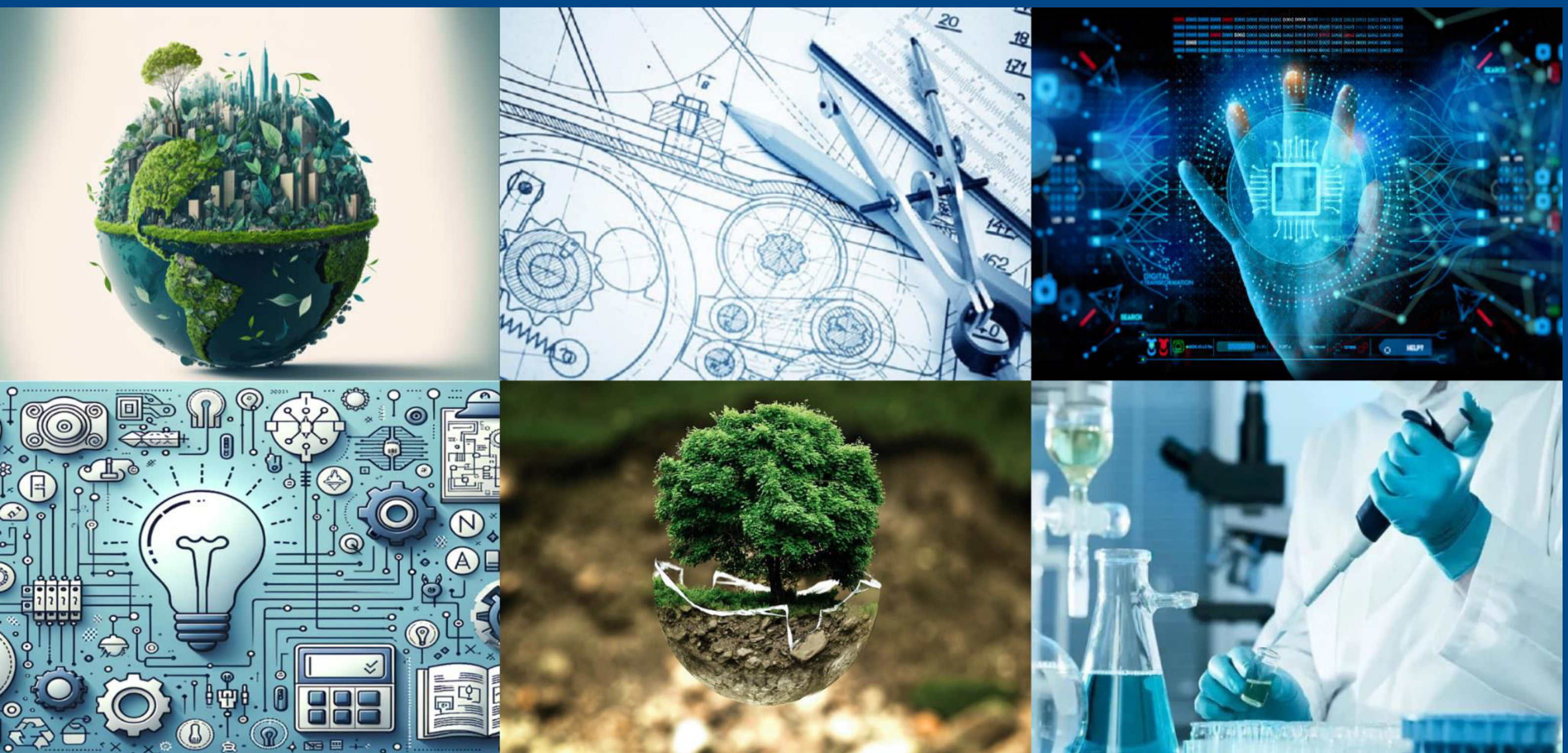

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Vehicle Number Plate Detection using YOLOv8

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ABSTRACT: Automatic number plate detection plays a crucial role in modern traffic management, security enforcement, and smart transportation systems. This project presents a real-time detection system leveraging YOLOv8, a state-of-the-art deep learning model. Traditional methods often struggle with challenges like poor lighting, occlusions, and motion blur, but YOLOv8 overcomes these limitations with its anchor-free architecture and optimized feature extraction. The system processes images, videos, and live camera feeds, enabling real-time previews, mid-process stopping, and efficient output storage. Performance evaluation through precision, recall, and mean average precision (mAP) confirms the system's effectiveness, making it a robust solution for automated number plate recognition in diverse conditions.

KEYWORDS: YOLOv8, Number Plate Detection, Deep Learning, Real-Time Processing

I. INTRODUCTION

Automatic number plate detection has become an essential component of modern traffic management, law enforcement, and security surveillance. With the rapid increase in the number of vehicles on the roads, conventional methods such as edge detection and template matching often struggle to provide accurate results due to challenges like varying lighting conditions, motion blur, and occlusions. To overcome these limitations, deep learning-based techniques have emerged as a reliable and efficient solution.

This project utilizes YOLOv8, a state-of-the-art object detection model, to enhance the accuracy and efficiency of vehicle number plate detection. YOLOv8's advanced architecture eliminates the need for predefined anchor boxes, making it more adaptable to real-world scenarios. Its improved backbone network and optimized loss functions allow for faster and more precise detections compared to earlier YOLO versions. The system is designed to work with images, videos, and live camera feeds, providing real-time results with the flexibility to stop processing midway and store outputs for later analysis.

To ensure high detection performance, the model is trained on a custom dataset featuring diverse vehicle and number plate conditions. Various data augmentation techniques, such as brightness adjustments, rotation, and noise addition, are applied to improve generalization. Additionally, the system integrates real-time visualization and storage capabilities, making it a practical choice for traffic surveillance and security applications.

By leveraging deep learning and real-time processing, this project aims to develop a scalable and robust vehicle number plate detection system. The integration of YOLOv8 offers significant improvements over traditional methods, enabling more accurate and efficient detection in dynamic environments, ultimately contributing to smarter transportation and law enforcement solutions.

II. LITERATURE SURVEY

The Numerous techniques have been proposed for vehicle number plate detection, focusing on locating the plate region, enhancing image quality, segmenting characters, and performing recognition. The field of Automatic Number Plate Recognition (ANPR) has made significant advancements, with researchers exploring various deep learning-based methods to enhance accuracy and efficiency.

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Rayudu Sushma's research introduced an ANPR system based on YOLOv4, addressing key challenges such as memory consumption and processing speed in real-time applications. The study demonstrated improved efficiency in license plate detection compared to conventional approaches.

A team of researchers, including Falguni Verma, Firoz Khan, Farhan Gupta, Faisal Johri, and Fiza Patel, explored the application of YOLOv5 in ANPR systems. Their work showcased the potential of YOLO-based models for high-speed and accurate license plate detection in various environmental conditions.

Mohammed Umer Farooq and his research team, comprising Saad Ahmed, Mustafa Latif, Danish Jawaid, Muhammad Zofeen Khan, and Yahya Khan, conducted a study integrating EasyOCR into ANPR systems. Their research focused on improving character recognition from license plates, demonstrating the effectiveness of deep learning models for extracting alphanumeric data with high precision.

Recent advancements with YOLOv8 have introduced an anchor-free architecture, optimized feature extraction, and improved detection accuracy. While previous studies have explored YOLOv4 and YOLOv5, research on YOLOv8's application in number plate detection remains limited.

Building on these studies, this project focuses on implementing YOLOv8 for vehicle number plate detection, leveraging its advanced object detection capabilities to enhance speed, accuracy, and real-time performance. The integration of YOLOv8 aims to set a new benchmark in ANPR technology by improving detection efficiency in complex real-world scenarios.

III. PROPOSED METHODOLOGY

This study presents an efficient approach for vehicle number plate detection using deep learning. The methodology is structured into four key phases: dataset preparation, model training, model testing, and deployment. The system is designed to handle static images, recorded videos, and real-time camera feeds while ensuring high accuracy and computational efficiency.

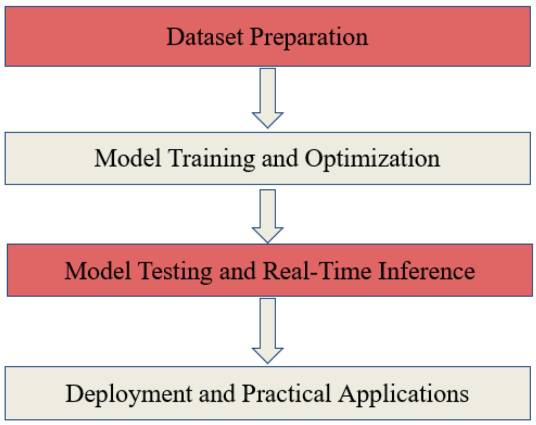

Figure 1: Proposed Methodology for Vehicle Number Plate Detection

1. Dataset Preparation

A dataset of **300 images** was compiled from diverse sources, including traffic surveillance footage and manually captured images. To facilitate model training, bounding box annotations were applied using the **LabelImg** tool in the YOLO-compatible format. The dataset was partitioned into **training (70%), validation (20%), and testing (10%)** subsets to ensure effective learning and performance evaluation.

To enhance model robustness, various preprocessing and augmentation techniques were applied. The images were first resized to a standardized dimension of 640×640 pixels to maintain consistency with the YOLOv8 model. Augmentation

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techniques, including rotation, brightness adjustments, noise addition, and flipping, were introduced to create variations and improve the model's generalization ability. Additionally, normalization was performed by scaling pixel values, which helps stabilize the model training process and optimize detection accuracy..

2. Model Training and Optimization

The YOLOv8n model, known for its efficiency in real-time object detection, was selected for this study. The model underwent training for **100 epochs**, using an image resolution of **640×640 pixels**. The dataset was configured using data.yaml, and training was optimized to balance accuracy and processing speed.

During training, several key improvements were observed. The box loss was reduced from 4.5 to 1.5, resulting in enhanced bounding box precision. Similarly, the class loss decreased from 6.0 to 1.5, reflecting improved classification accuracy. The Distribution Focal Loss (DFL) also declined from 4.5 to 1.5, leading to increased prediction confidence. The model's performance was evaluated using standard object detection metrics, achieving a precision of 0.8, a recall of 0.6, and a mean Average Precision (mAP) of 0.8 at both mAP50 and mAP50-95 thresholds, indicating 80% precision.

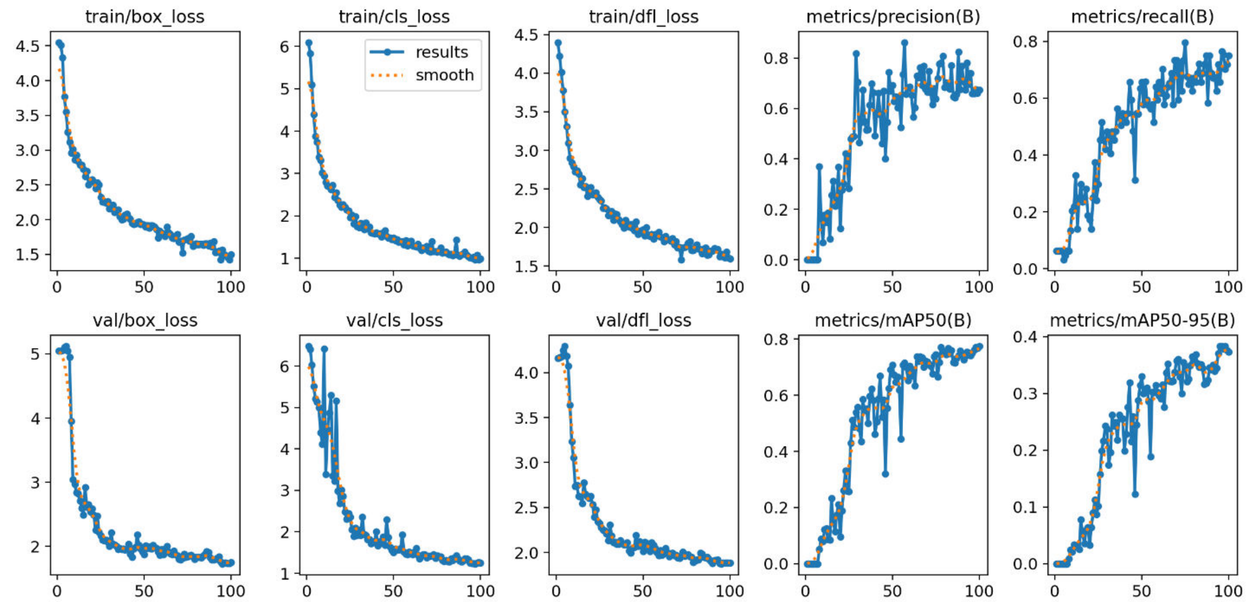

Figure 2: Training and Validation Metrics

3. Model Testing and Real-Time Inference

The trained model was tested across **three different input modalities** to evaluate its adaptability to real-world scenarios:

Static Image Detection: The model was applied to standalone images to verify its capability in detecting number plates under varying lighting and occlusion conditions.

Video-Based Detection: Pre-recorded video sequences were processed to analyze detection accuracy under dynamic conditions.

Live Camera Feed Analysis: Real-time detection was conducted using a webcam or surveillance camera, allowing immediate identification of number plates.

4. Deployment and Practical Applications

To ensure practical usability, the detection model was equipped with several important functionalities. It provided a real-time preview of detected number plates, enabling immediate analysis and quick verification of results. This feature

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allowed users to monitor the detection process as it happened, enhancing the model's effectiveness in real-world scenarios.

Additionally, the model included a mid-process stopping option, giving users the flexibility to halt the detection process at any point while securely storing intermediate results. It also ensured that all detected frames and extracted number plate information were automatically saved for future analysis and reference, making the system reliable and user-friendly for post-processing tasks.

IV. Testing and Results

The proposed vehicle number plate detection system was evaluated through extensive testing to determine its accuracy and reliability. The performance was assessed using a confusion matrix, which provides insights into the model's classification ability. Additionally, the system was tested across three different scenarios: static images, pre-recorded video footage, and live camera feeds to ensure its effectiveness in real-world conditions.

The confusion matrix (Figure 3) provides an overview of the model's performance. The system correctly detected 77% of the license plates (True Positives) and missed 23% (False Negatives). It accurately identified background elements 100% of the time (True Negatives) and made no incorrect detections (False Positives: 0%). The overall accuracy of the model is 88.5%, showing strong performance in real-world conditions.

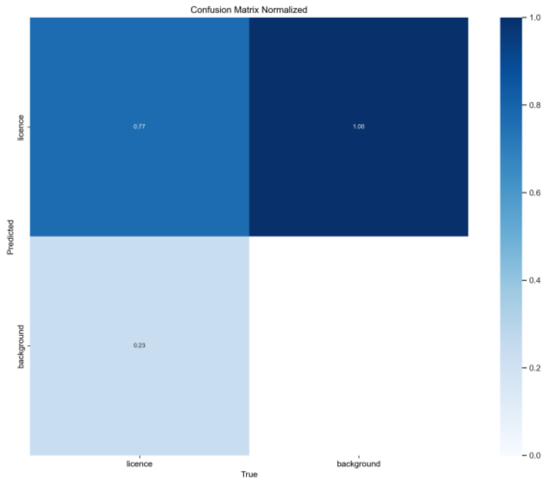

Figure 3: Normalized Confusion Matrix

The model performance is evaluated using multiple metrics to understand the trade-offs between precision, recall, and confidence. These metrics help in assessing how well the model performs under different confidence thresholds and provide insights for optimization.

Figure 4(a) represents the Recall-Confidence Curve, which shows how recall decreases as confidence increases. This highlights the balance between capturing more instances and maintaining certainty in the predictions. A higher confidence threshold reduces false positives but may also miss some correct detections.

Figure 4(b) illustrates the Precision-Recall Curve, demonstrating the inverse relationship between precision and recall. A higher precision often comes at the cost of reduced recall, making this metric crucial for optimizing model performance based on specific application needs. The curve helps determine the best trade-off for the given problem.

Figure 4(c) presents the Precision-Confidence Curve, depicting how precision improves with increasing confidence levels, though at the expense of reducing the number of detected instances. Figure 4(d) shows the F1-Confidence Curve, which helps determine the optimal confidence threshold that balances precision and recall.

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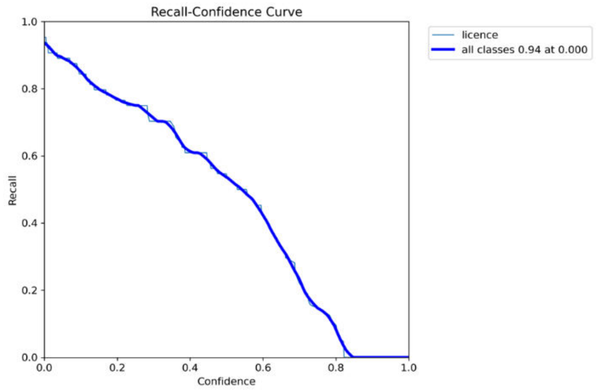

Figure 4(a)

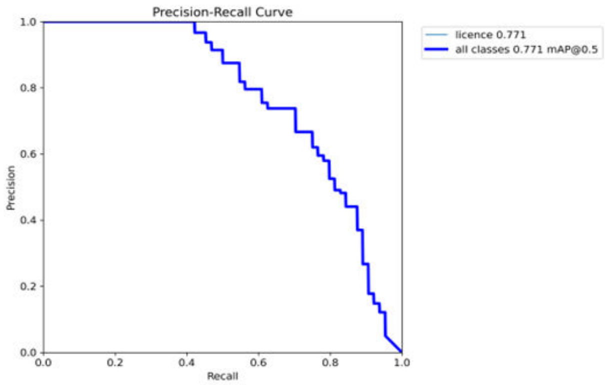

Figure 4(b)

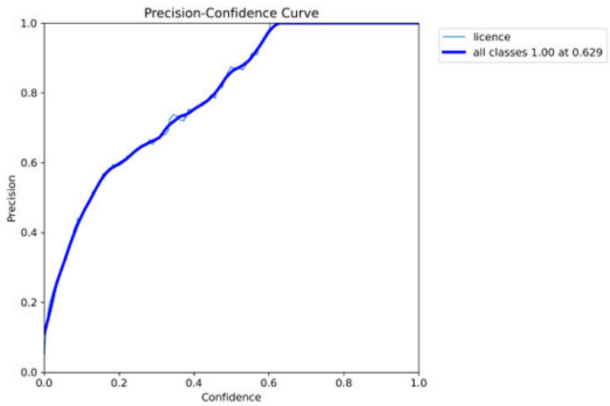

Figure 4(c)

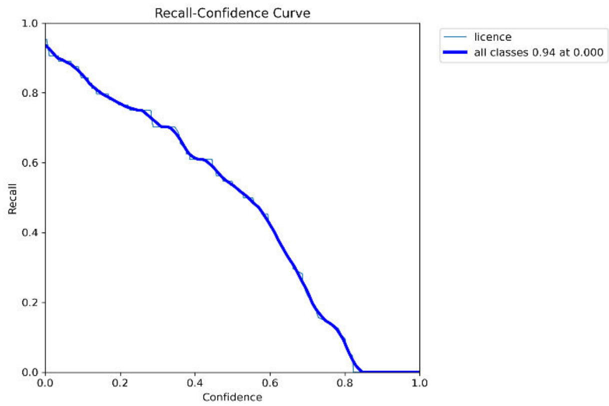

Figure 4(d)

Figure 4: Performance Metrics – (a) Recall-Confidence Curve, (b) Precision-Recall Curve, (c) Precision-Confidence Curve, (d) F1-Confidence Curve.

Detection on Static Image

In Figure 5, the system successfully detects the number plate of a stationary vehicle. The blue bounding box accurately encloses the plate region with a confidence score of **0.69**. This high confidence value indicates the model's effectiveness under controlled and clear conditions.

Figure 5: Static Image

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Detection on Video Frame

Figure 6 demonstrates the detection result on a video frame where a moving vehicle is involved. The number plate is correctly localized with a confidence score of **0.60**, which is appreciable considering the challenges introduced by motion blur and changing viewpoints. This confirms the model's potential for real-time video applications

Figure 6: based on video

Detection on Camera Feed

Figure 7 presents the output from a real-time camera feed. Despite complex backgrounds, varying lighting conditions, and vehicle motion, the model detects multiple number plates with confidence scores of **0.30** and **0.33**. While the confidence is comparatively lower, it still indicates the system's capability to detect number plates in practical, dynamic environments.

Figure 7: Camera Feed

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V. CONCLUSION

This project demonstrates the effective application of YOLOv8 for vehicle number plate detection, providing a robust and efficient solution for real-time applications. Utilizing advanced deep learning techniques, the system ensures high accuracy even under challenging conditions such as varying lighting and occlusions.

The integration of preprocessing steps and the YOLOv8 model enhances detection precision. This comprehensive approach streamlines the workflow, ensuring seamless processing of both image and video inputs.

Overall, this project highlights the potential of combining Python and state-of-the-art deep learning frameworks to automate vehicle number plate detection. It serves as a foundation for developing more advanced systems that can further enhance traffic monitoring, law enforcement, and automated toll collection.

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